# Optimal Budget Allocation of Health Care Resources for End Stage Renal Disease

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## Abstract

End-stage renal disease (ESRD) has been a widespread disease in many countries, especially in Taiwan. According to the statistics of United States renal data system (USRDS), Taiwan had high rates of incident ESRD and the greatest rates of prevalent ESRD in 2008. Moreover, with the increasing ESRD patients appear, the huge expense becomes a heavy burden in the society. To avoid deterioration, the government proposes many incentive programs to stimulate better medical quality and the ultimate goal is to reduce the incident and prevalent rates of ESRD. In this study, we develop a continuous-time Markov chain model to estimate the patients' life expectancy and their disease progression of ESRD individually under different scenarios. Besides, we propose a mathematical model which is constructed to allocate resources to incentive programs to maximize patients' life expectancy under the limited funds. The results provide suggestions to the government for allocating resources to achieve optimal patients' effectiveness.

## Keywords
End stage renal disease, continuous-time Markov chain model, budget allocation model.

## 1. Introduction

Chronic kidney disease (CKD) occurs when one's kidney function is gradually losing over time and the decrease of kidney function is permanent. With loss of kidney function, CKD is divided into five stages. Table 1 lists the five stages of CKD and their corresponding symptoms and severity. The stage 5 of CKD is also referred to end stage renal disease (ESRD) is the failure of kidney function. Patients with ESRD are unable to remove fluid, electrolytes, and biologic products from body. Unlike acute renal failure, this kind of renal failure is irreversible, which means that patients with ESRD will not recover anymore. Patients with ESRD must rely on hemodialysis (HD), peritoneal dialysis (PD) or kidney transplantation to maintain their lives.

**Table 1: Stages of CKD**

| Stage | Symptoms and severity | GFR(ml/min/1.73m2) |
|---|---|---|
| 1 | Normal kidney function and micro albuminuria | More than 90 |
| 2 | Mild decrease in kidney function and micro albuminuria | 60-89 |
| 3 | Moderate decrease in kidney function | 30-59 |
| 4 | Severe decrease in kidney function | 15-29 |
| 5 | Kidney failure | Less than 15 |

Data resources: National Kidney Foundation (2011)

Due to the increasing number of ESRD patients, research on ESRD has been paid more attention in recent years. Many publications such as Johansen *et al*. (2009), Teerawattananon *et al*. (2007), Tang *et al*. (2010) and Lee et al. (2008) have compared the survival rate, hospitalization rate, complications disease incidence rate and cost-effectiveness of different treatments or different dialysis strategies. Chang (2006) proposes a discrete-time Markov model which analyzes the cost-effectiveness of treatments and constructs a health-care resources allocation model to optimize the patients' benefits. Some studies like Lee *et al*. (2008) model the progression of ESRD and used it to find the relationship between the timing of dialysis initiation and the therapy's cost and effectiveness.

The purpose of this study is to realize the progression of ESRD of individual and estimate the influence of interventions like incentive programs proposed by the government and try to determine the way to allocate health-care resources to achieve better medical quality for CKD and ESRD patients in Taiwan. In the following text, we will raise a problem statement and present the methodology about progression model of ESRD from a patient perspective by using Markov model in Section 2. Afterwards, we will construct a budget allocation model in order to optimize the patients benefit. The computational results of the progression of ESRD for patient and budget allocation model will be presented in Section 3. Finally, conclusions will be made in Section 4.

## 2. Model Constructions

In this section, the problem statement and the progression model of ESRD will be stated and the optimal budget allocation model will be proposed. Firstly, the problem statement will be presented in Section 2.1. Then, we will provide a continuous-time Markov model to describe the progression of ESRD in Section 2.2. After describing the ESRD progression of patients, the optimal budget allocation model is formulated in Section 2.3. In addition, some incentive programs created to enhance quality of care for the CKD and ESRD patients will also be introduced.

### 2.1 Problem Statement

In Taiwan, there are more and more people get ESRD per year and they could not survive more than a few months without treatments like HD, PD or kidney transplantation. Owing to the increasing number of ESRD patients, the medical expenses become a huge burden of society. Hence, we need to realize the present status of them in order to control the future situation and try to estimate the effects of incentive programs. Furthermore, we attempt to figure out how to allocate health care resources efficiently to maximize patients' effectiveness. Note that because the majority of dialysis patients choose HD as their treatments and data regarding to PD are limited or not available in Taiwan, therefore, we assume that each dialysis patient will accept HD in this study.

### 2.2 Methodology

When time goes by, CKD patients may experience the decreasing function of kidney, dialysis or get the transplantation. Hence, we create four states in continuous-time Markov model and take the early conditions of CKD into account in our model. Besides, we assume any transition time to another state is exponential. Our proposed four states are described as follows:

$S_1$ the decreasing function of kidney before dialysis: This is a transient state.
$S_2$ the decreasing function of kidney after dialysis: This is a transient state.
$S_3$ transplantation: This is a transient state.
$S_4$ death: This is an absorbing state.

Figure 1 is a diagram of the continuous-time Markov model. Patient enters this model when his/her kidney function starts to degenerate, and he/she will follow the pathways, marked in arrows, based on transition probability densities to progress to other states.

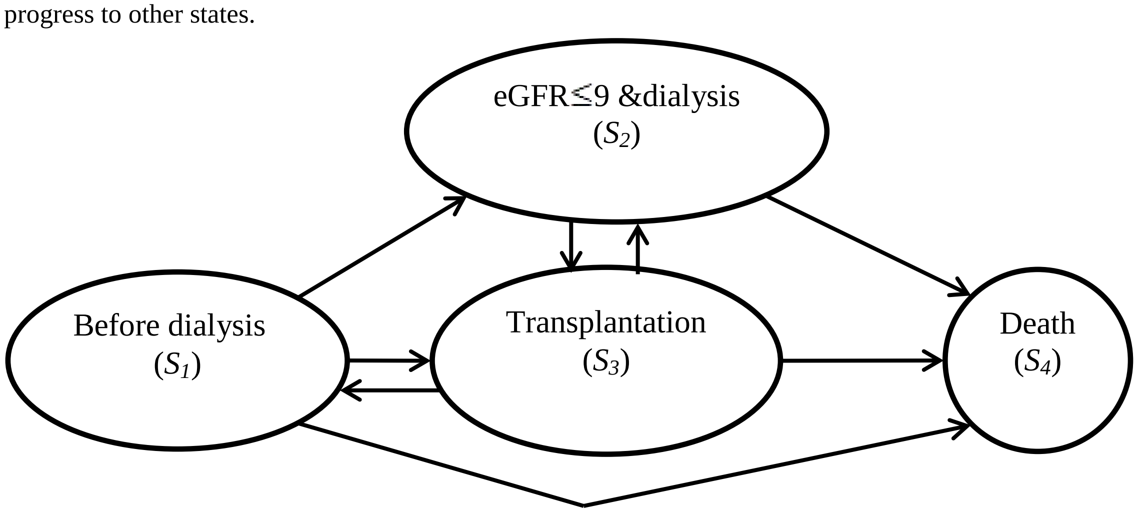


Figure 1: Graphical Representation for Markov model of ESRD

It is obviously that the model of the ESRD progression is an absorbing continuous-time Markov chain and we can expect the ESRD patient life expectancy after knowing the transition probability densities of the patient which is provided by Lee *et al.* (2006). Kemeny and Snell (1960) and Logofet and Lensnaya (2000) clearly explained how to find the life expectancy in a continuous-time Markov chain. Take patient $i$ for example, the transition density matrix of patient $i$ is in the following form:

$$\Lambda_i = \begin{bmatrix} \lambda_{i11} & \lambda_{i12} & \lambda_{i13} & \lambda_{i14} \\ \lambda_{i21} & \lambda_{i22} & \lambda_{i23} & \lambda_{i24} \\ \lambda_{i31} & \lambda_{i32} & \lambda_{i33} & \lambda_{i34} \\ \lambda_{i41} & \lambda_{i42} & \lambda_{i43} & \lambda_{i44} \end{bmatrix}, \tag{1}$$

and the fundamental matrix for patient $i$ is as follows:

$$N_i = (I-Q)^{-1} = (-\Lambda_i{}')^{-1} = \left( -\begin{bmatrix} \lambda_{i11} & \lambda_{i12} & \lambda_{i13} \\ \lambda_{i21} & \lambda_{i22} & \lambda_{i23} \\ \lambda_{i31} & \lambda_{i32} & \lambda_{i33} \end{bmatrix} \right)^{-1}. \tag{2}$$

And the time to absorption, that is, the life expectancy of patient $i$ in our research is represented to

$$TA_i = E(t) = \pi' \left( -\begin{bmatrix} \lambda_{i11} & \lambda_{i12} & \lambda_{i13} \\ \lambda_{i21} & \lambda_{i22} & \lambda_{i23} \\ \lambda_{i31} & \lambda_{i32} & \lambda_{i33} \end{bmatrix} \right)^{-1} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \tag{3}$$

where $\pi'$ is the initial probability vector records the distribution of the ESRD patients pool on different transient states $S_1$, $S_2$ and $S_3$. Considers the different initial conditions of patients, it enables us to get the more practical results of the expected life expectancy of patient $i$.

However, the ESRD progression model is from a patient perspective. Hence, in order to grasp the current status of the overall population of these patients in Taiwan, we will use a patient generation model as described below to generate a representative CKD and ESRD patients' pool in Taiwan. Firstly, we collect the data in order to analyze the attributes' distribution of patients including age, gender, blood type, comorbid conditions and nutrition indicators. Secondly, the patient generation model generates hypothetical patients according to the proportion of these attributes and we assume these attributes are inter-independent in our study. Thirdly, we generate hypothetical patients of sample size $H$ which is enough to represent the overall population of these patients. Finally, we collect every sampled patient's results as the current CKD and ESRD patients' performance.

Next, how to efficiently distribute the health care resources to incentive programs proposed to promote the medical quality of CKD and ESRD patients under budget constraints will be discussed.

### 2.3 Model Framework for Budget Allocation

For the reason of improving the medical quality of CKD and ESRD patients, the government proposed many incentive programs in Taiwan. Subject to the budget constraint, every program will not be fully implemented. Here, we use the mathematical programming to solve the problem of how to efficiently allocate the health care resources to optimize the patients' effectiveness under the budget constraints. The incentive programs will be introduced and the mathematical programming model will be constructed subsequently. The introduction of the incentive programs are presented as follows:

- Program of the improvement on the medical payments for early CKD. This program is aimed at the patients in the early stage of CKD. By the active management of the disease, it is effective to prevent or postpone the deterioration of kidney function. The estimated effect of program 1 will decrease the transition probability density $\lambda_{12}$ by $q_1$.
- Pre-ESRD preventive program. This program is aimed at the patients in Stage 3, 4 and 5 of CKD as shown in Table 1.1 and it is combined with cross-professional medical teams to establish the integral care system

for patients with CKD and the goal is to reduce the ESRD incident rates. The estimated effect of program 2 will decrease the transition probability density $\lambda_{12}$ by $q_2$.

- Reward program for enhancing the quality of dialysis services. This program is set for dialysis patients. By the monitoring of the indicators for the quality of dialysis services, the medical conditions will be improved and dialysis patients can enjoy the better quality of life. The estimated effect of program 3 will increase the transition probability density $\lambda_{22}$ by $q_3$.

After knowing these incentives and their estimated effects, the parameters and variables are illustrated as follows:

- In order to represent the overall population of CKD and ESRD patients, we have to analyze the results of patients of sample size $H$ as the overall performance.
- In order to achieve the goal of promoting better medical quality and lengthening patients' life years, the government provides the total budget $B$ for these programs and let $c_j$ be the fully implementing cost of program $j$ ($j$ = 1, 2, 3). Certainly, the total budget $B$ must be less than the sum of $c_j$. It is noteworthy that the values of $c_j$ and $B$ are represented relatively, which means that the values of $c_j$ and $B$ are not real.
- In this study, we use the continuous-time Markov chain to model the progression of ESRD from a patient perspective. Therefore, the decision variables will respond to the individual setting. Let $x_{ij}$ be the binary variables and $x_{ij} = 1$ if patient $i$ receives program $j$ ($j$ = 1, 2, 3) and $x_{ij} = 0$ otherwise.
- Subject to the budget constraint, every program will not be fully implemented, Hence, let $u_j$ be the percentage implemented of program $j$ ($j$ = 1, 2, 3). If $u_j = 0.5$, it means that the half of patients will receive program $j$ and others won't.
- Let $TA_i$ be the estimated life years of patient $i$ before implementing the programs and it can be calculated by (3).
- Let $TP_i$ be the estimated life years of patient $i$ after implementing the programs and it can be represented as

$$TP_i = \pi'\left(-\begin{bmatrix} \lambda_{i11} + q_1 x_{i1} + q_2 x_{i2} & \lambda_{i12} - q_1 x_{i1} - q_2 x_{i2} & \lambda_{i13} \\ \lambda_{i21} & \lambda_{i22} + q_3 x_{i3} & \lambda_{i23} \\ \lambda_{i31} & \lambda_{i32} & \lambda_{i33} \end{bmatrix}\right)^{-1} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \qquad (4)$$

  where $\pi'$ has the same definition as above, and $q_j$ ($j$ = 1, 2, 3) represents the estimated effects of program $j$ on transition probability densities and we assume the effects on transition probability densities are the same among different patient. In addition, $TP_i$ is uncertain until the decisions of $x_{ij}$.

Due to the increasing number of ESRD patients, the government proposed many incentive programs to improve the medical quality for them. In this thesis, we try to find the best implementing levels of these incentive programs to maximize the patients' effectiveness by using the mathematical programming. Now, we are going to present the optimal budget allocation model. It can be divided into two major parts: the objective function and the budget constraints. The objective is to maximize patients' effectiveness, i.e., the average of sample size $H$ patients' extended life years after implementing programs. However, the sum of implementing cost of these programs is limited within the total available budget. The mathematical form of this budget allocation problem is as follows:

$$\text{MAX} \quad \frac{[\sum_{i=1}^{H} TP_i - TA_i]}{H} \qquad (5)$$

$$\text{s.t.} \quad \sum_{i=1}^{H} x_{ij} \le H \cdot u_j \text{, for } j = 1, 2, 3 \qquad (6)$$

$$\sum_{j=1}^{3} c_j u_j \le B \qquad (7)$$

$$u_j \le 1 \text{, for } j = 1, 2, 3 \qquad (8)$$

$$x_{ij} \in (0, 1) \tag{9}$$

We can solve it by an optimization modeling software, LINGO, and find the optimal implementing proportion of these incentive programs which maximize the patients' effectiveness. Therefore, we can figure out the optimal combination of incentive programs. We will present a case study next.

## 3. Numerical Analysis

In this section, we focus on the numerical analysis of optimal budget allocation model proposed by Section 2. Firstly, we will list some basic settings of optimal budget allocation model and a case study will be shown in Section 3.1. Then, the effects of different attributes on patient survival performance will be discussed in Section 3.2.

### 3.1 Case Study

Before showing the case study, we will introduce the settings of parameters. Table 2 lists the proportions of attributes we are interested in, and it is the basis of our patient generation model. Next, the estimates for the transition probability densities and the adjustments depending on attributes are presented in Table 3.

Table 2: Attributes and the corresponding classes

| Attributes | | Distribution |
|---|---|---|
| Age | <50 | 16.40% |
| | 50-59 | 24.56% |
| | 60-69 | 28.92% |
| | 70-79 | 19.93% |
| | >=80 | 10.19% |
| Gender | Male | 51.53% |
| | Female | 48.47% |
| Blood type | O | 43.57% |
| | A | 26.65% |
| | B | 23.72% |
| | AB | 6.06% |
| Diabetes | Yes | 43.00% |
| | No | 57.00% |
| Heart disease | Yes | 14.80% |
| | No | 85.20% |
| Cancer | Yes | 4.80% |
| | No | 95.20% |
| Serum albumin | Yes | 11.32% |
| | No | 88.68% |

Data resources: United States Renal Data System (2010), Taiwan Society of Nephrology (2010)

Besides, Table 4 lists the initial probabilities for all transient states and the effects, costs of the three incentive programs and the total budget available to carry out these incentive programs. However, the size of patient pool is unknown. Therefore, we have to determine an appropriate size of patient pool. It is noteworthy that the complexity will arise when the patient pool size increases. Moreover, the optimal budget allocation model in our study is nonlinear, so the optimal value in local will be different from in global. Hence, the solving type of local or global should be decided before the determination of patient pool size. According to our results, local and global performances are very close but the average running time in different size solved in local are less than in global especially when the size >= 40. Consequently, we decide to use local way to solve our model. Then, we conduct ten experiments in every different patient pool size respectively to determine the size of patient pool. It is obvious that

Table 3: Estimations of the coefficients for transition probability densities

| Attributes | | $\lambda_{13}$ | $\lambda_{14}$ | $\lambda_{23}$ | $\lambda_{24}$ | $\lambda_{31}$ | $\lambda_{32}$ | $\lambda_{34}$ |
|---|---|---|---|---|---|---|---|---|
| Intercept | | 7.56 | 6.90 | 8.40 | 5.51 | 10.92 | 8.73 | 9.74 |
| Age | 50-59 | | 0.11 | | 0.11 | -0.02 | -0.02 | -0.77 |
| | 60-69 | | -0.21 | | -0.21 | -0.22 | -0.22 | -1.17 |
| | 70-79 | | -0.50 | | -0.50 | -0.22 | -0.22 | -1.17 |
| | >=80 | | -1.17 | | -1.17 | -0.22 | -0.22 | -1.17 |
| Gender | Female | 0.13 | 0.20 | 0.13 | 0.20 | | | 0.04 |
| Blood type | A | -0.41 | | -0.41 | | 0.02 | 0.02 | 0.03 |
| | B | 0.12 | | 0.12 | | 0.03 | 0.03 | 0.03 |
| | AB | -0.79 | | -0.79 | | -0.02 | -0.02 | 0.03 |
| Diabetes | Yes | | -0.11 | | -0.11 | | | |
| Heart disease | Yes | | -0.40 | | -0.40 | | | |
| Cancer | Yes | | -0.69 | | -0.69 | | | |
| Serum albumin < 3.6 g/dL | Yes | | -0.81 | | -0.81 | | | |
| Transition rate in | Yes | Days | Months | Days | Months | Days | Days | Days |

Data resources: Lee *et al.* (2006)
Note:

1. *The transition probability densities are calculated by this equation* $e^{-(\alpha+\beta y)}$. *The row marked "Intercept" gives the coefficient* $\alpha$ *, and the other rows give the coefficients* $\beta$ *regarding modifications caused by different attributes and y is a vector representing the attributes.*
2. $\lambda_{21}$, $\lambda_{41}$, $\lambda_{42}$ *and* $\lambda_{43}$ *are equal to 0 because of the irreversibility of CKD and absorption of death, so they are not appeared above.*
3. - : *denotes that the attributes shows insignificance in that transition probability density and we take the value as zero in our model.*
4. $\lambda_{12}$ *= exp(-2.8). It is calculated based on Levey et al.* (*1988*), *because it is not provided by Lee et al.* (*2006*).

Table 4: Estimations of parameters

| Parameters | | Notations | Predict value |
|---|---|---|---|
| Initial probability for transient state | Before dialysis | π'$_1$ | 0.992 |
| | Dialysis | π'$_2$ | 0.0074 |
| | Transplantation | π'$_3$ | 0.0006 |
| Effect on transition rate of program | 1 | $q_1$ | 0.0024 |
| | 2 | $q_2$ | 0.001 |
| | 3 | $q_3$ | 0.0004 |
| Cost of program (relative value) | 1 | $c_1$ | 320 |
| | 2 | $c_2$ | 84 |
| | 3 | $c_3$ | 45 |
| Total budget | | $B$ | 359.2 |
| Data resources: Bureau of National Health Insurance (2011), Department of Health, Executive Yuan, R.O.C (2011), Wen *et al.* (2008). | | | |

Output will be more reliable when the size is >= 60. However, the model will be more complicated and time spent to solve the model will lengthen when the size is large. Based on the tradeoff between reliability and time considerations, we determine the size = 60.

With the information above, a case study of $H$ = 60 can be conducted. The first step is to generate 60 hypothetical patients in patient pool. Next, put them into our optimal budget allocation model and observe the implementation levels of these programs and the optimal value. From the optimal results, the implementation level of program 3, $u_3$, is the highest with value = 1, which means that every patient will receive program 3. The implementation levels of program 1 and 2 are relatively low compared to program 3, which means that not every patient will receive program 1 and 2. So, we can conclude that program 3 is the most worthy program to promote. Besides, the optimal value, the average of 60 patients' extended life years after implementing programs, is 13.25 months. It represents that these patients can enjoy the extended 13.25 months averagely when the budget is allocated in accordance with the optimal solution.

### 3.2 The Effect of Different Attributes

In order to analyze the effects of attributes on patients, we will compare the patients' life performances between two or more groups which have opposite or different level settings of one specific attribute. It should be noted that the other attributes remain the same as case study for easily observation.

We compare five attributes of patients including age, diabetes, heart diseases, cancer and serum albumin level. The results reflected in Table 5 indicate that some points are worth noting. Firstly, age has great impact not only on patients' life expectancies before implementing incentive programs but also on the extended life years after these programs. Secondly, diabetes, heart disease and cancer will cause significant impacts on patients' life expectancies. In other words, patients with comorbidity conditions will enjoy less benefit than patients without comorbidity conditions. Thirdly, the serum albumin level, nutritional indicators, will also affect a lot on patients' life years and effectiveness of these programs. Finally, it summarizes information for us that low serum albumin level may impact patients' life years and effectiveness of incentive programs more than cancer and heart disease.

Table 5: Results of experiments with different setting of attributes

| Attributes | Setting | $u_1$ | $u_2$ | $u_3$ | Before program (months) | Extended (months) | Percentage of extended |
|---|---|---|---|---|---|---|---|
| Origin | - | 0.75 | 0.88 | 1.00 | 233.11 | 13.25 | 5.68% |
| Age | <50 | 0.73 | 0.93 | 1.00 | 387.48 | 30.15 | 7.78% |
| | 50-59 | 0.77 | 0.82 | 1.00 | 291.84 | 19.08 | 6.54% |
| | 60-69 | 0.75 | 0.88 | 1.00 | 203.31 | 10.09 | 4.97% |
| | 70-79 | 0.75 | 0.88 | 1.00 | 175.03 | 7.26 | 4.15% |
| | >80 | 0.75 | 0.88 | 1.00 | 113.74 | 2.91 | 2.56% |
| Diabetes | Yes | 0.75 | 0.88 | 1.00 | 227.08 | 12.58 | 5.54% |
| | No | 0.75 | 0.88 | 1.00 | 239.80 | 14.14 | 5.90% |
| Heart disease | Yes | 0.75 | 0.88 | 1.00 | 189.31 | 8.34 | 4.41% |
| | No | 0.75 | 0.88 | 1.00 | 237.83 | 13.82 | 5.81% |
| Cancer | Yes | 0.75 | 0.88 | 1.00 | 154.49 | 5.39 | 3.49% |
| | No | 0.75 | 0.88 | 1.00 | 233.80 | 13.27 | 5.67% |
| Serum albumin | Low | 0.75 | 0.88 | 1.00 | 145.45 | 4.67 | 3.21% |
| | High | 0.75 | 0.88 | 1.00 | 237.33 | 13.60 | 5.73% |

## 4. Conclusions

In this paper, a continuous-time Markov chain is presented to model the progression of ESRD and it is created from a patient perspective because the transition probability densities between the four states including before dialysis, dialysis, transplantation and death are modified by patients attributes. Besides, we generate a representative CKD and ESRD patients' pool and put these patients into the progression model in order to grasp the current status of the overall population of CKD and ESRD patients in Taiwan. Furthermore, we construct a mathematical programming model combined with the progression of ESRD model for the aim of finding the best way of allocating health care resources to maximize the patients' effectiveness.

Some of findings in our study are worth summarizing. Firstly, we can judge that the incentive program 3 is the most valuable one to carry out according to the implementing levels provided by optimal solution under the assumption that our estimated parameters are reliable. The more likely explanation rests in the fact that patients in Taiwan are not aware of the seriousness until their conditions become severely degenerated, so the incentive program 1 and 2 which are designed for the patients without dialysis appear to less effective. Secondly, attributes of patients have significant impact not only on their life expectancies before implementing incentive programs but also on the effectiveness of implementing these programs. It is believed that the healthier patient enjoys more effectiveness than the less healthy one even though they have the same resources and this is consistent with our finding. Besides, we can calculate the quantified difference of survival performances between different groups of patients by controlling the attributes in our study.

Most importantly, we construct an optimal budget allocation model to give trusted output which can provide suggestions to the government for allocating resources to achieve optimal patients' effectiveness as long as the estimations of parameters are reliable and accurate. However, there are some limitations in acquiring data of CKD and ESRD patients in Taiwan and it is the reason that the outputs are not so robust. Concerning the limitations above, we lists some future work and extensions of this research in the following directions:

- Parameter estimations of transition probability densities in Taiwan. In order to provide a more accurate continuous-time Markov chain model to describe the progression of ESRD, the parameters of transition probability densities are worthy investigating and being determined until the survival data of CKD and ESRD patients are available in Taiwan.
- The reality of the effects on transition probability densities of incentive programs. The effects on transition probability densities of incentive programs are assumed to be the same even though the attributes of patients varied in our study. The investigation of effects on transition probability densities modified by patients' attributes would be an interesting topic for further research.
- The involvement of PD in the ESRD progression model. Be limited by the data resource of PD patients, PD is not considered in this research. We suggest that future research should extend by adding a PD state in the ESRD progression model when the data with regard to PD patients are obtainable.

In conclusion, this research presents preliminary results of a pilot model and gives a general framework of optimal budget allocation model combined with the outputs ESRD progression model from a patient perspective. We propose a reliable foundation for decision makers of government to allocate health care resources and hope CKD and ESRD patients to gain better quality of medical care and enjoy longer life years.

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